AUTOMATIC OPTIC DISK LOCALIZATION IN RETINAL IMAGES

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Abstract-**The optic disk is the exit point of the retinal nerve fibers from the eye, and the entrance and exit point for retinal blood vessels. It is a brighter region than the rest of the ocular fundus and its shape is approximately round. The location of the optic disk is crucial in retinal image analysis, for example, as a reference to measure distances and identify anatomical parts in retinal images (e.g. fovea), for blood vessel tracking, and many others. Previous work on the optic disk has mainly focused on locating its center only. The aim of this study is accurately locating the optic disk and well defining its contour fully automatically. The proposed algorithm is based on morphological operations and snakes for precise optic disk localization. The initial contour for a snake must be close to the desired boundary otherwise it converges to the wrong place. Hence, automatically positioning a suitable initial snake is a crucial step.**
***Keywords* - Optic disk, retinal image, image processing, snakes**

I. INTRODUCTION

Retinal image is a highly specialized form of medical imaging. A fundus camera is a specialized low power microscope with an attached camera. Its optical design is based on the indirect ophthalmoscope. The photographer can visualize the back of the eye by focusing light through the cornea, pupil and lens.

Most of the trials on the optic disk mainly focused on locating its center only [1, 2, 3]. Cox et al. [4] used gray level information around the vicinity to automatically extract the boundary of the optic disk with initial approximate location given by the user input. Osareh et al. [5] build their method on template matching and dynamic contour to determine the boundary of the optic disk.

The proposed algorithm consists of different image processing techniques starting with the digital color retinal image and the final result is fully automated precise localization of the optic disk boundary.

II. METHODOLOGY

Retinal Image Data Acquisition

The captured fundus images were obtained using a TOPCON TRC-501A non-mydiatric fundus camera, with a Sony CCD video camera attached to system. The captured fundus image is a 570x570x24 bits color digital image. Fig. 1, shows an example.

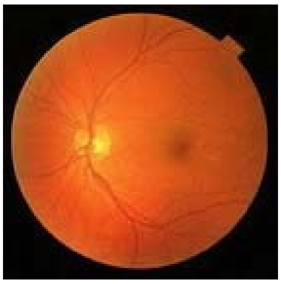


Fig. 1. Color retinal image.

RGB and HIS Color Models

The RGB color model (where R, G, and B are abbreviated from the colors Red, Green, and Blue respectively) is used, in this work, to display the color retinal image, and in the background elimination step, while the HSI color model (where H, S, and I are abbreviations for Hue, Saturation, and Intensity respectively) is used in the all subsequent processing stages. The RGB and HSI have an invertible relation between them [6].

Background Elimination

The optimum threshold technique [6] is applied to the red component image, to make the pixels belonging to the fundus image region and the pixels belonging to the dark surrounding region separable. The optimum threshold is calculated using the following iterative algorithm:

1. Assuming no knowledge about the exact location of fundus region, consider as a first approximation that the four corners of the image contain background pixels only, and the remainder contains fundus pixels.
2. At step t, compute μ_B^t and μ_F^t as the mean background and fundus gray level respectively, where segmentation into background and fundus at step t is defined by the threshold value T^t determined in the previous step.
$$\mu_B^t = \frac{\sum_{(x,y)\in background} I_R(x,y)}{\# background\_pixels} \quad (1)$$
$$\mu_F^t = \frac{\sum_{(x,y)\in fundus} I_R(x,y)}{\# fundus\_pixels} \quad (2)$$
where: $I_R(x,y)$ is the red intensity of the pixel (x,y) in the color image.
3. Set $T^{(t+1)} = \frac{\mu_B^t + \mu_F^t}{2}$ which provides an updated background/fundus distinction.
4. If $\left|T^{(t+1)} - T^{(t)}\right| < epson$ then halt; otherwise go to step (2). Where epson is a small number like one or two.

Local Contrast Enhancement

Because the fundus is not a plane (spherical face), the illumination is uneven. The brightness of objects and background in central region is usually higher than that in the

surrounding region. As a result, the contrast of the fundus images tends to diminish as the distance of a pixel from the center of the image increases. Hence a preprocessing contrast enhancement is needed to reduce this effect.

Let $f(x,y)$ be the intensity image of the color retinal image. Consider a sub image window $w(x,y)$ centered on a pixel located at (x,y). Suppose that f_{max} and f_{min} are the maximum and minimum intensities of the whole image. Denote the mean and standard deviation of the intensity within W by $\mu_w(f)$ and $\sigma_w(f)$ respectively. The adaptive contrast enhancement transformation [2] is defined by:

$$f(x,y) \to g(x,y) = 255 \frac{[\phi_w(f) - \phi_w(f_{\min})]}{[\phi_w(f_{\max}) - \phi_w(f_{\min})]} \quad (3)$$

where the sigmoid function is

$$\phi_w(f) = \left[1 + \exp\left(\frac{\mu_w(f) - f}{\sigma_w(f)}\right)\right]^{-1} \quad (4)$$

After applying this transformation, the areas with initially small intensity standard deviations (poor contrast) will show more details. However, this will also increase the noise. Hence 2D Gaussian smoothing filter [6] has been applied in order to reduce the noise before the local contrast enhancement process. Fig. 2, shows the integer valued convolution mask that approximates a Gaussian with a σ of 1.4.

Region of Interest (ROI) Identification

The optic disk is typically found in a region that occupies approximately 80x80 pixels. The appearance is characterized by a relatively rapid variation in intensity because the "dark" blood vessels are beside the "bright" nerve fibers. The adjacent pixels intensity variance is used for initial detection of the optic disk center [2].

Let $g(x,y)$ be the resultant intensity image of previous processing step (contrast enhancement) and $w(x,y)$ be a sub image window centered on a pixel located at (x,y). A variance image is formed by the transformation:

$$p(x,y) = \mu_W(g^2) - \mu_W^2(g) \quad (5)$$

An image $q(x,y)$ of the average variance within the sub images is then obtained as:

$$q(x,y) = \mu_w(p) \quad (6)$$

The point (x_d,y_d) with the maximum of this image is taken as an initial estimation of the center of the optic disk. Then a square region of interest (ROI) is constructed such that the point (x_d,y_d) is in its center. The size of this sub image is taken 110x110 pixels to ensure containing the entire area of the optic disk.

	2	4	5	4	2
	4	9	12	9	4
$\frac{1}{115}$	5	12	15	12	5
	4	9	12	9	4
	2	4	5	4	2

Fig. 2. Gaussian filter with σ = 1.4.

Initial Estimation of the Optic Disk Contour

The Hough transform [6] is a technique which can be used to isolate features of a particular shape within an image. Because it requires that the desired features be specified in some parametric form, the circular Hough transform can be used for the initial approximate detection of the optic disk as a nearly circular object in the fundus image. The motivating idea behind the Hough technique for circle (the approximation of the optic disk) detection is that each input measurement (e.g. coordinate point) indicates its contribution to a globally consistent solution. A circle can be described by the parametric equation:

$$(x - x_d)^2 + (y - y_d)^2 = r^2 \quad (7)$$

where x_d and y_d are the coordinates of the center of the circle and r is the radius. The transform is implemented by quantizing the Hough parameters space into finite intervals or accumulator cells. (i.e. a multidimensional array). As the algorithm runs, each (x_i,y_i) in the estimated "ROI" is transformed into a discretized (x_d, y_d, r) and the accumulator cells which satisfy Eq. (7) are incremented. Peaks in the accumulator array represent strong evidence that a corresponding circle exists in the image. Computational load can be reduced by using the edge's gradient direction vector. The center of a circle lies on a line along the gradient vector direction. This reduces the update to two points at each radius [7, 8].

However, the actual optic disk contour is not pure circular in shape. So, to identify accurately the actual contour of the optic disk, active contour models or snakes technique is applied.

Blood Vessels Removal

Active contour models are often called snakes because they appear to slither across images (a phenomenon known as hysteresis). This method works on a gradient image and lock onto homogeneous regions enclosed by strong gradient information. In the fundus image and to use snakes for accurately locating the optic disk contour, this task is made extremely difficult since the optic disk region is invariably fragmented into multiple regions by blood vessels. This is why further processing is required before applying the snake method.

The "ROI" is processed by two morphological operations to remove the regions of blood vessels that are found on the optic disk to create fairly constant region. This is done by applying morphological closing operation, i.e. a dilation process [6] to first remove the blood vessels and then an erosion process [6] to restore the boundaries to their former position.

Precise Localization of the Optic Disk

Active contour method [9,10] turns the problem of edge detection and linking into an energy minimization problem. Typically, the traditional way of edge detection consists of applying a gradient operator to the image and then linking the found, often non-continuous, edges. The active contour model works the other way around. First a continuous initial contour

or curve model is formed (the circle of optic disk approximation found previously by the Hough transform method). Then internal and external forces act on the model drawing the curve to an equilibrium position which will be the accurate optic disk contour.

Because of the way the active contour models behave while minimizing their energy they are also called "snakes". Fig. 3, shows a snake with its ends joined so that it forms a closed loop. Over a series of time steps the snake moves into alignment with the nearest salient feature (in this case an edge). The contour is influenced by the following forces:

1. Internal forces: internal constraints give the model tension and stiffness.
2. External forces: external constraints come from high-level sources such as human operators or automatic initialization procedures.
3. Image forces: image energy is used to drive the model towards salient features such as light and dark regions, edges, and terminations.

The total energy of the model (E_{snake}) is given by the sum of the energy for the individual snake elements (vertices 'v'):

$$E_{snake} = \int E_{internal}(v) + \int E_{external}(v) + \int E_{image}(v) \quad (8)$$

The internal energy of a snake element is defined as:

$$E_{internal}(v) = \alpha(s)|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2 \quad (9)$$

This energy contains a first-order term controlled by $\alpha(s)$, and a second-order term controlled by $\beta(s)$. The first-order term makes the snake contract like an elastic band by introducing tension, while the second-order term makes it resist bending by producing stiffness. Adjusting the weights $\alpha(s)$ and $\beta(s)$ controls the relative importance of the tension and stiffness terms.

The external energy term is used to control attraction or repulsion forces that drive active contour to or from specified features. These forces are easily found by differentiation. The gradient vector flow [9,10] provides the external force necessary to push the initial circular active contour toward the actual contour of the optic disk.

III. Results & Discussion

It is found that the red component of the color retinal image is the most suitable for the background elimination step. Fig. 4, is the resultant binary image after the background elimination of the color fundus image shown in Fig. 1.

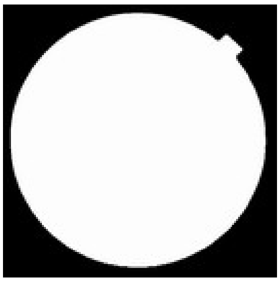


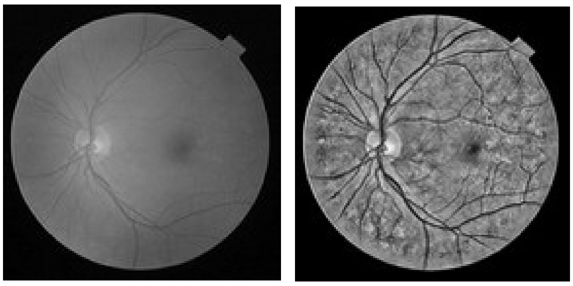
Fig. 4. The result of the background elimination step.

After eliminating the black background from the fundus image, the color retinal image is converted to an intensity image ("I" component of the HSI model). Then, the contrast of the intensity image is enhanced by applying the locally adaptive contrast enhancement transformation method. The intensity images before and after contrast enhancement are shown in Fig. 5.

As shown in Fig. 5 (b), the optic disk is in a region of nearly 80x80 pixels and its appearance is characterized by a relatively rapid variation in intensity because the "dark" blood vessels are beside the "bright" nerve fibers. Using this phenomenon and Equations (5, 6) the "ROI" is localized from processing the image shown in Fig. 5 (b). Fig. 6, shows the result of the localization of "ROI" (labeled by black square) superimposed on the original color retinal image of Fig. 1.

The rest of the processing steps are applied only to the resultant "ROI" to reduce the processing time and not to generate a false initial contour for the snake, especially in the images of patients suffering from "diabetic retinopathy".

The step of determining a circular approximation of the optic disk using the circular Hough transform is performed to obtain an initial contour for the snake method. Fig. 7, shows



(a) (b)

Fig. 5. Retinal intensity images (a) before (b) after contrast enhancement.

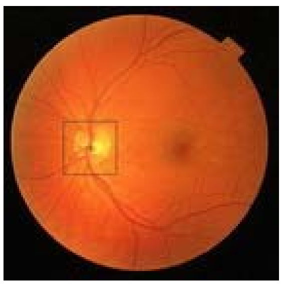


Fig. 6. The localization of the "ROI".

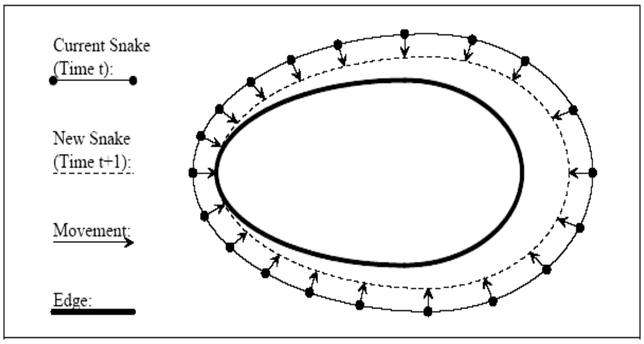


Fig. 3. A closed active contour model.

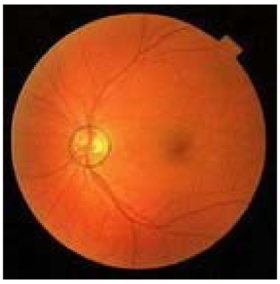


Fig. 7. The localization of initial contour for the snake.

the result of the determination of the initial snake (black circle) superimposed on the original color retinal image of Fig. 1.

Because of the snake locks onto homogeneous regions enclosed by strong gradient information, the "ROI" part of the enhanced image shown in Fig. 5 (b), is processed by the "closing" morphological operation (dilation then erosion) to remove the regions of blood vessels that are found on the optic disk to create fairly constant region before applying the snake method. Fig. 8, shows the result (N.B. The "ROI" part is zoomed to show clearly the fairly constant region after applying the morphological closing operation).

Finally the active contour algorithm is applied for accurately locating the optic disk and the result (the optic disk contour) is shown in Fig. 9(b). Comparing this result with Fig. 9 (a) (which shows the "ROI" part of the original color retinal image shown in Fig. 1), it is noticeably that, a perfect contour is obtained that accurately well define the optic disk.

IV. Conclusion

The identification of the optic disk contour is an important task in many ophthalmic applications. The color retinal image is fully automated till reaching the exact contour of the optic disk. The background is eliminated, then the intensity image is enhanced to increase its contrast. The location of the optic disk center is defined to locate a suitable region of interest

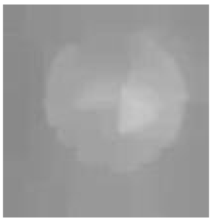
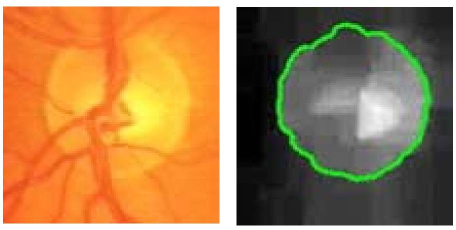


Fig. 8. Removing blood vessels in "ROI".



(a) (b)

Fig. 9. Final localization of the optic disk.

"ROI". The rest of the processing steps are applied only to this region. This reduces the processing time, prevents from defining a false initial contour, and makes it suitable for the online applications, e.g. retinal identification. In the "ROI" an initial circular snake is automatically estimated to be used as an initial contour in the active contour method. Morphological operations are crucial before applying the active contour method. Finally the exact contour of the optic disk is determined.

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